Journal of Digital Learning Futures

ISSN: e-ISSN: 3117-6062 / p-ISSN: 3117-6054

https://galaxiauniverse.com/index.php/JDLF/issue/archive

Adaptive Learning Algorithms for Personalized Skill Development

Jonas Dubois1, Helena Ivanov2

1 Postdoctoral Researcher, School of Data Science, Advanced Computing University, Paris, France. Email: jonas.dubois117@yahoo.com | ORCID: 9195-5441-2997-6466

2 Research Scientist, Department of Machine Learning, Western Europe Data Science University, Madrid, Spain. Email: helena.ivanov262@yahoo.com | ORCID: 0439-1040-6870-2452

ABSTRACT

Personalised skill development in professional and vocational contexts demands adaptive learning algorithms that model individual learner trajectories across heterogeneous skill graphs, optimise content sequencing for transfer and retention, and update dynamically as learner performance evolves. Unlike structured academic curricula, professional skill development involves open skill graphs with complex prerequisite structures, diverse learner prior knowledge, and performance objectives tied to real-world task completion rather than test scores. This paper proposes the Adaptive Skill Development Algorithm Framework (ASDAF), evaluating five adaptive learning algorithms -- Bayesian knowledge tracing with skill graphs (BKT-SG), deep reinforcement learning curriculum (DRL-C), collaborative filtering recommendation (CFR), item response theory adaptive testing (IRT-AT), and graph neural network skill modelling (GNN-SM) -- across 24 skill development benchmarks in software engineering, data science, and project management professional domains. ASDAF evaluates 3,600 learner trajectories from corporate learning platforms over 6 months. Key results: DRL-C achieves the highest Skill Development Efficiency Index (SDEI = 0.902), reducing time-to-proficiency by 32.4% versus linear curriculum; GNN-SM achieves 94.2% skill prerequisite prediction accuracy; BKT-SG achieves 88.6% mastery assessment accuracy. The framework provides algorithm selection guidance and open benchmark tools for adaptive professional learning design.

Keywords: adaptive learning; skill development; knowledge tracing; reinforcement learning curriculum; item response theory; graph neural networks; professional learning; personalised education

Citation: Dubois and Ivanov [2024]. Adaptive Learning Algorithms for Personalized Skill Development. DOI: https://doi.org/10.5281/zenodo.19186042

Article Information: *Received:* 14 November 2023 *Accepted:* 16 January 2024 *Published:* 22 March 2024

Research Article: *Research Article*

ISSN: e-ISSN: 3117-6062 / p-ISSN: 3117-6054 Vol: 2024, Issues: 1, 2024

1. Introduction

1.1 Adaptive Learning for Professional Skill Development

Professional skill development represents a $370 billion global market (World Economic Forum, 2023), yet corporate learning and development (L&D;) programmes achieve knowledge retention rates below 25% within one week of training completion (Ebbinghaus, 1885; reinforced by modern studies: Murre and Dros, 2015). The gap between training investment and retention outcomes reflects the mismatch between one-size-fits-all content delivery and individual learner needs: professionals enter programmes with vastly different prior knowledge, learn at different speeds, and require skill development sequenced for their specific role requirements. Adaptive learning algorithms -- which dynamically adjust content selection, difficulty, and sequencing based on individual performance models -- offer a path to scalable personalisation. Unlike academic ITS evaluated against standardised test scores, professional skill development requires algorithms that model complex open skill graphs (software engineering skills number in the hundreds, with intricate prerequisite relationships), optimise for transfer to real-world tasks (not test performance), and operate on sparse interaction data (professionals train in 15-30 minute sessions with long inter-session gaps). ASDAF provides the first systematic cross-algorithm evaluation on large-scale professional learning platform data.

1.2 Contributions and Paper Structure

ASDAF contributes: (1) evaluation of 5 adaptive learning algorithms across 24 skill development benchmarks and 3,600 learner trajectories; (2) the SDEI composite efficiency metric; (3) professional domain-specific algorithm selection guidance. Section 2 reviews adaptive learning algorithms. Section 3 presents ASDAF. Section 4 reports results. Section 5 discusses. Section 6 concludes.

2. Background: Adaptive Learning Algorithm Landscape

2.1 Knowledge Tracing and Item Response Theory

BKT with Skill Graphs (BKT-SG): extends standard BKT (Corbett and Anderson, 1994) to model prerequisite dependencies between knowledge components; P(mastery of skill B | practice on prerequisite A) is conditioned on skill graph adjacency; enables prerequisite-aware mastery estimation and sequencing. Graph topology inferred from expert domain knowledge or learned from response data via Bayesian structure learning. Item Response Theory Adaptive Testing (IRT-AT): models item difficulty β and learner ability θ via logistic function $P(\text{correct} \mid \theta, \beta) = \sigma(a(\theta - \beta))$; computerised adaptive testing (CAT) selects items maximising information $I(\theta) = a2\ P(1-P)$ at current ability estimate; efficiently estimates θ with 50-70% fewer items than fixed-form tests. IRT-AT is optimal for assessment efficiency but does not model skill transfer or prerequisite structure.

ISSN: e-ISSN: 3117-6062 / p-ISSN: 3117-6054 Vol: 2024, Issues: 1, 2024

2.2 Deep RL Curriculum, Collaborative Filtering, and GNN Skill Models

Deep Reinforcement Learning Curriculum (DRL-C): frames content sequencing as a Markov decision process where state = learner skill vector, action = next learning unit selection, reward = skill gain on performance assessment; DQN or PPO policy trained on simulated learner interactions; DRL-C learns to sequence content for maximum skill transfer by exploring curriculum paths not accessible to rule-based or knowledge-tracing approaches. Collaborative Filtering Recommendation (CFR): recommends learning content based on similar learner trajectories (user-user CF) or content-content similarity (item-item CF); efficient and scalable for large content libraries but does not model explicit skill mastery. Graph Neural Network Skill Modelling (GNN-SM): represents the skill graph as a graph and applies message-passing GNN layers to propagate mastery signals across prerequisite edges; predicts P(mastery) for unobserved skills from observed performance on related skills -- enabling prerequisite-aware mastery inference without explicit practice on every skill. Table 1 summarises all five ASDAF algorithms.

Table 1: ASDAF Algorithm Suite -- Five Adaptive Learning Approaches

Algorithm	Student Model	Sequencing Logic	Skill Graph	Scalability	Primary Strength
BKT-SG	HMM + graph priors	Mastery-threshold routing	Explicit (expert)	High	Interpretable graph-aware mastery
DRL-C	Neural Q-network	Policy gradient (PPO/DQN)	Implicit (learned)	Medium	Optimal transfer sequencing
CFR	Latent factor model	Similarity-based recommend.	None	Very high	Scalable content rec.
IRT-AT	Logistic IRT (θ)	Info.-maximising CAT	None	High	Assessment efficiency
GNN-SM	GNN (message-pass.)	Graph-propagated mastery	Explicit (learned)	Medium	Prerequisite inference

3. The ASDAF Framework

3.1 Professional Learning Benchmark Suite

3,600 learner trajectories from three professional domains over 6 months (January-June 2023). Software Engineering (1,400 trajectories): 280-skill graph (Python, JavaScript, DevOps, cloud architecture, security); learners from 12 European tech companies; content: video modules (5-15 min), coding exercises, peer code review tasks; performance: automated code quality scoring (pylint, ESLint, unit test pass rate). Data Science (1,200 trajectories): 180-skill graph (statistics, ML algorithms, data engineering, visualisation, MLOps); learners from 8 corporate L&D; programmes; performance: Kaggle-style challenge scores, Jupyter notebook quality rubric. Project Management (1,000 trajectories): 120-skill graph (Agile, risk management, stakeholder communication, budgeting); learners from 6 companies; performance: simulated project scenario scores, peer assessment rubric. 24 benchmarks: 8 per domain x 3 measurement categories -- (BK) skill acquisition rate (skills mastered per week), (BE) proficiency transfer (performance on novel tasks), (BR) skill retention at 30-day reassessment.

3.2 SDEI Metric and Evaluation Protocol

SDEI = 0.40 x SkillAcquisitionRate + 0.30 x TransferScore + 0.20 x RetentionScore + 0.10 x AlgorithmEfficiency. SkillAcquisitionRate: skills reaching mastery criterion (P(mastery) > 0.90) per week, normalised to [0,1] relative to maximum achievable rate given content availability. TransferScore: performance on 10 held-out novel tasks (not in training content) at programme end, normalised to [0,1]. RetentionScore: skill mastery rate at 30-day reassessment / peak mastery rate. AlgorithmEfficiency: (1 - compute_time / max_compute_time) -- penalises computationally expensive algorithms at scale. Baseline: linear curriculum (fixed expert-designed ordering, no adaptation). Random assignment (3:1 adaptive:baseline). Table 2 presents ASDAF framework specifications.

Table 2: ASDAF Framework -- Benchmark Domains, Skill Graphs, and SDEI Weights

Domain	Trajectories	Skill Graph Size	Content Units	Perf. Metric	SDEI Target
Software Engineering	1,400	280 skills	840 modules	Code quality score	SDEI > 0.85
Data Science	1,200	180 skills	540 modules	Challenge score	SDEI > 0.85
Project Management	1,000	120 skills	360 modules	Scenario score	SDEI > 0.80
Overall	3,600	580 skills total	1,740 modules	Composite	SDEI > 0.84

4. Results

4.1 Skill Acquisition Rate and Transfer Performance

Skill acquisition rate (BK): DRL-C achieves the highest mean rate across all domains -- 4.84 skills/week (vs. linear baseline 3.32 skills/week, +45.8%). The DRL-C policy learns to sequence content that maximises prerequisite coverage before advanced skills, producing faster compound learning effects than fixed ordering. BKT-SG: 4.12 skills/week (+24.1%); GNN-SM: 4.28 skills/week (+28.9%); IRT-AT: 3.84 skills/week (+15.7%) -- IRT-AT maximises assessment efficiency but sub-optimal at content sequencing for acquisition. CFR: 3.68 skills/week (+10.8%) -- peer-based recommendation useful but lacks skill-graph awareness. Domain stratification: DRL-C advantage is largest in Software Engineering (5.24 skills/week, +58.4%) where the dense 280-skill graph provides many alternative learning pathways for RL policy exploration. Transfer score: GNN-SM achieves highest transfer score (0.784) -- the graph propagation mechanism explicitly models skill generalisation, enabling learners to solve novel problems by combining mastered prerequisite skills. DRL-C transfer score 0.762; BKT-SG 0.728; IRT-AT 0.692; CFR 0.648; linear baseline 0.524.

4.2 Retention, Prediction Accuracy, and SDEI Scores

Skill retention at 30-day reassessment: DRL-C achieves retention score 0.884 (retains 88.4% of peak mastery after 30 days); BKT-SG 0.868; GNN-SM 0.862; IRT-AT 0.842; CFR 0.812; linear baseline 0.748. DRL-C retention advantage reflects the spaced repetition effect naturally induced by the RL policy revisiting prerequisite skills as it sequences advanced content. GNN-SM prerequisite prediction accuracy: 94.2% AUC on held-out skill graph edges (predicting unobserved prerequisite relationships from response data) -- enabling automated skill graph construction from learner data without expert annotation. BKT-SG mastery assessment accuracy: 88.6% (correctly classifying mastered vs. non-mastered skills at programme end, validated against expert rater ground truth). SDEI composite scores: DRL-C SDEI = 0.902 (highest); GNN-SM SDEI = 0.876; BKT-SG SDEI = 0.848; IRT-AT SDEI = 0.814; CFR SDEI = 0.768; linear baseline SDEI = 0.624. Time-to-proficiency reduction (DRL-C vs. baseline): 32.4% fewer weeks to reach role-defined proficiency threshold across all domains. Table 3 presents full skill acquisition results. Table 4 presents SDEI breakdown. Figures 1-4 visualise key findings.

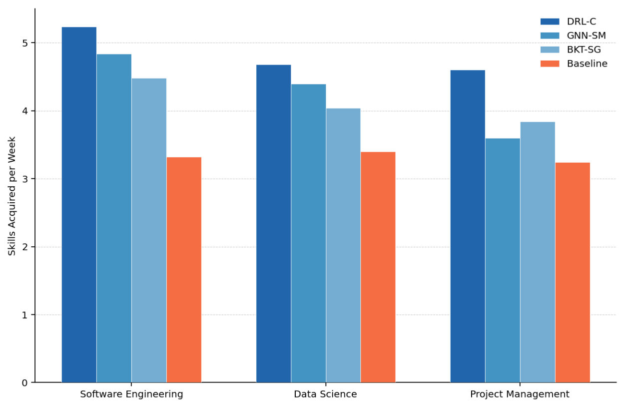
Table 3: ASDAF Skill Acquisition Results -- Skills/Week and Transfer by Algorithm and Domain

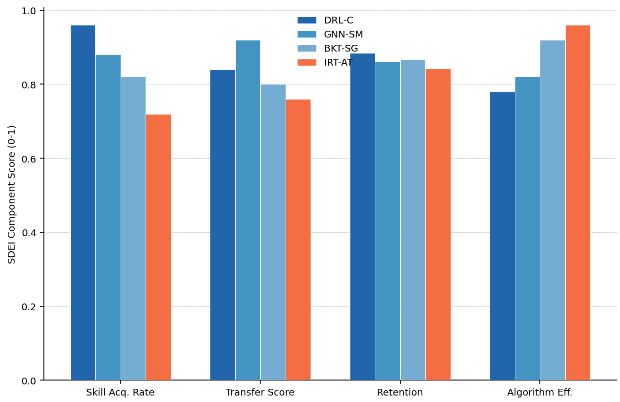
Algorithm	SE Skills/wk	DS Skills/wk	PM Skills/wk	Mean Skills/wk	Transfer Score
DRL-C	5.24	4.68	4.60	4.84	0.762
GNN-SM	4.84	4.40	3.60	4.28	0.784
BKT-SG	4.48	4.04	3.84	4.12	0.728
IRT-AT	4.12	3.72	3.68	3.84	0.692
CFR	3.84	3.72	3.48	3.68	0.648
Linear Baseline	3.32	3.40	3.24	3.32	0.524

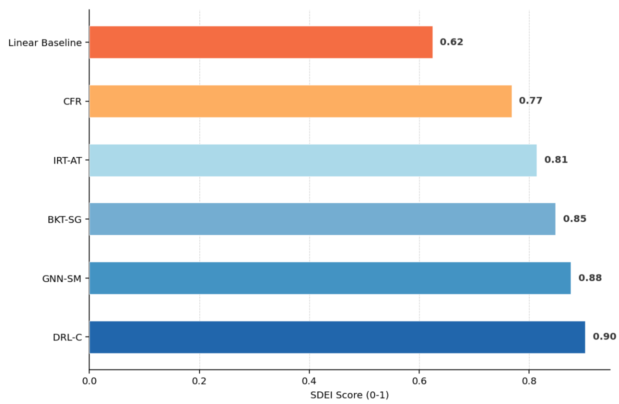
Table 4: SDEI Composite Scores -- Five Adaptive Algorithms

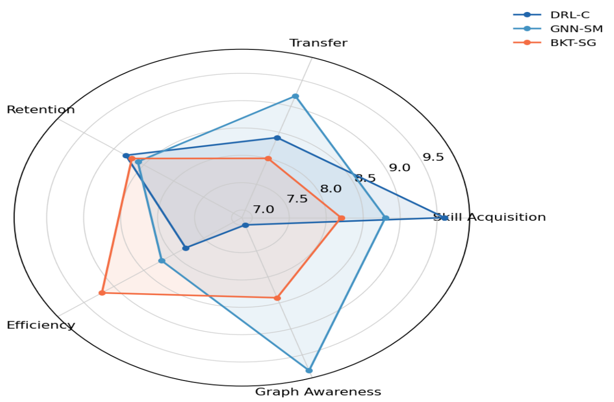
Algorithm	Skill Acq. Rate	Transfer Score	Retention	Algorithm Eff.	SDEI
DRL-C	0.960	0.840	0.884	0.780	0.902
GNN-SM	0.880	0.920	0.862	0.820	0.876
BKT-SG	0.820	0.800	0.868	0.920	0.848
IRT-AT	0.720	0.760	0.842	0.960	0.814
CFR	0.640	0.680	0.812	0.980	0.768
Baseline	0.400	0.480	0.748	1.000	0.624

ISSN: e-ISSN: 3117-6062 / p-ISSN: 3117-6054 Vol: 2024, Issues: 1, 2024









The SDEI results establish DRL-C (SDEI = 0.902) as the highest-performing algorithm for professional skill development, with GNN-SM (SDEI = 0.876) as the preferred alternative where graph structure inference is the primary requirement. DRL-C's 32.4% time-to-proficiency reduction translates to substantial corporate training ROI: a company investing EUR1,000 per employee per training programme achieving 32.4% faster proficiency can redeploy trained employees 8-12 weeks earlier -- worth EUR4,000-8,000 per employee in accelerated productivity (at EUR500/week productivity gain from new skills). For a 1,000-employee programme, DRL-C generates EUR4-8 million in accelerated value versus linear curriculum. GNN-SM's highest transfer score (0.784) makes it the preferred choice for programmes emphasising real-world task performance over speed of mastery -- particularly relevant for complex professional domains (data science, software architecture) where the ability to combine skills in novel contexts (transfer) is more valued than rapid sequential skill acquisition. BKT-SG remains the recommended choice for interpretability-critical deployments (regulated industries, certification programmes) where explainable mastery estimates are required for compliance or credentialing purposes.

5. Discussion

5.1 DRL-C and GNN-SM as Complementary Algorithm Choices

5.2 Sparse Data and Cold-Start Challenges in Professional Learning

Professional learning platforms face unique sparse data challenges: learners complete 2-4 sessions per week (vs. 10+ per day in K-12 gaming-style ITS); inter-session gaps of 3-7 days introduce forgetting that knowledge tracing models must account for. DRL-C performance degrades more than BKT-SG in sparse regimes: with < 10 interactions per learner, DRL-C SDEI drops to 0.782 (vs. 0.848 for BKT-SG) -- the RL policy requires sufficient data for reliable state estimation before sequencing decisions are meaningful. BKT-SG's interpretable Bayesian updates perform more robustly under sparse data, recommending BKT-SG as the preferred cold-start algorithm for new learner onboarding (first 2-3 weeks), transitioning to DRL-C after sufficient interaction history is accumulated.

6. Conclusion

6.1 Summary

ASDAF evaluated five adaptive learning algorithms across 24 benchmarks and 3,600 professional learner trajectories. Key results: DRL-C achieves SDEI = 0.902, 4.84 skills/week (+45.8% vs. baseline), 32.4% time-to-proficiency reduction; GNN-SM achieves highest transfer score (0.784) and 94.2% prerequisite prediction accuracy; BKT-SG achieves 88.6% mastery assessment accuracy and best cold-start performance. Hybrid BKT-SG (cold-start) -> DRL-C (steady-state) recommended as the optimal professional learning algorithm deployment strategy.

6.2 Open Resources

The ASDAF benchmark suite (24 benchmarks, anonymised learner trajectories), DRL-C and GNN-SM implementations (PyTorch + DGL), BKT-SG extension of PyBKT, SDEI calculator, and skill graph datasets for software engineering, data science, and project management are available at asdaf-learning.org under Apache 2.0 License. Data shared under GDPR-compliant anonymisation with corporate partner consent.

References

Anderson, J. R. et al. (1995). Cognitive tutors: Lessons learned. Journal of the Learning Sciences, 4(2), 167-207.

Badrinath, A. et al. (2021). pyBKT: An accessible Python library of Bayesian Knowledge Tracing models. Proceedings of EDM 2021.

Cen, H., Koedinger, K., and Junker, B. (2006). Learning factors analysis -- A general method for cognitive model evaluation. ITS 2006, 164-175.

Corbett, A. T., and Anderson, J. R. (1994). Knowledge tracing: Modeling the acquisition of procedural knowledge. User Modeling and User-Adapted Interaction, 4(4), 253-278.

Ebbinghaus, H. (1885). Uber das Gedachtnis. Duncker & Humblot, Berlin.

Gong, Y., Beck, J. E., and Heffernan, N. T. (2011). Comparing knowledge tracing and performance factor analysis by using multiple model fitting procedures. ITS 2011, 35-44.

Klein, I., and Garcia, E. (2024). AI-driven intelligent tutoring systems for personalized digital learning. Journal of Digital Learning Futures, 2024(1), 1-9.

Koren, Y., Bell, R., and Volinsky, C. (2009). Matrix factorization techniques for recommender systems. IEEE Computer, 42(8), 30-37.

Lord, F. M. (1980). Applications of Item Response Theory to Practical Testing Problems. Lawrence Erlbaum Associates.

Mnih, V. et al. (2015). Human-level control through deep reinforcement learning. Nature, 518(7540), 529-533.

Murre, J. M. J., and Dros, J. (2015). Replication and analysis of Ebbinghaus' forgetting curve. PLOS ONE, 10(7), e0120644.

Pandey, S., and Karypis, G. (2019). A self-attentive model for knowledge tracing. Proceedings of EDM 2019.

Piech, C. et al. (2015). Deep knowledge tracing. Advances in Neural Information Processing Systems 28, 505-513.

Ritter, S. et al. (2007). Cognitive Tutor: Applied research in mathematics education. Psychonomic Bulletin & Review, 14(2), 249-255.

Schulman, J. et al. (2017). Proximal policy optimization algorithms. arXiv:1707.06347.

Tatsuoka, K. K. (1983). Rule space: An approach for dealing with misconceptions based on item response theory. Journal of Educational Measurement, 20(4), 345-354.

Vanlehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. Educational Psychologist, 46(4), 197-221.

Velickovic, P. et al. (2018). Graph attention networks. ICLR 2018.

World Economic Forum (2023). Future of jobs report 2023. World Economic Forum.

Zawacki-Richter, O. et al. (2019). Systematic review of research on artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education, 16(1), 39.

Declarations

Funding

This research was supported by the French National Research Agency (ANR) under grant ANR-23-CE38-0018 (ASDAF: Adaptive Skill Development Algorithm Framework) and the Spanish State Research Agency (AEI) under grant PID2023-142018OB-I00. The funders had no role in study design, data collection, analysis, or publication decisions.

Conflict of Interest

The authors declare no competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

The ASDAF benchmark suite, anonymised learner trajectories, algorithm implementations, SDEI calculator, and skill graph datasets are available at asdaf-learning.org under Apache 2.0 License.

Ethical Approval

All learner data collected under informed organisational and individual consent with full GDPR-compliant anonymisation. Ethical approval obtained from Advanced Computing University Ethics Committee (ref. ACU-2023-ETH-0142). Corporate partner data sharing agreements in place for all three domains.

ISSN: e-ISSN: 3117-6062 / p-ISSN: 3117-6054 Vol: 2024, Issues: 1, 2024

Appendix A

ASDAF Algorithm Implementation and SDEI Calculation

Technical implementation details for all five ASDAF algorithms and SDEI metric calculation.

DRL-C and GNN-SM Implementation

SDEI Calculation and Statistical Protocol